Face Recognition Based on LDA and SOM Neural Nets

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Abstract

The use of biometric technique for automatic personal identification is one of the biggest challenges in the security field. The process is complex, because it is influenced by many factors related to the form, position, illumination, rotation, translation, disguise and occlusion of face characteristics. This work presents a searching method to identify a face in a training database. We have proposed an algorithm for face recognition based on LDA subspace using a SOM neural net to memorize each class (face) in the stage of classification/identification. The interaction between the number of eigenvectors in the PCA and LDA subspaces has been analyzed to establish the rate recognition.

1 Introduction

The recognition of human faces is one area that searches to develop mathematical algorithms for authentication or identification extracting important characteristics for the recognition and directing the search in the database. Two of the most popular techniques in the face recognition are: Principal Components Analysis (PCA) and Linear Discriminant Analysis (LDA). In the literature we can find some works exploring the applications of LDA subspace in face recognition. [4], [8], [9] and [1] compared PCA with LDA subspace using some diversified face databases with innumerable situations (translation, scales, rotation, illumination, etc). [6], [7] and [3] analyzed the effect in face recognition that is related with the number of training samples.

In this work, we have implemented a face recognition algorithm applying LDA subspace with an intermediate PCA space and a set of SOM neural nets in the stage of classification. We hope that the SOM nets present a good results in the face memorization with soft light variations of rotation, because [5] has implemented SOM in the classification stage of face and satellite images.

1.1 PCA, LDA and SOM Neural Net

The PCA technique based on face recognition finds eigenvectors that constitute the face sub-space bases (eigenspace) that are gotten through the covariance matrix formed by the correlation between pixels. In summary, each image of a human face in the training set can be represented in terms of a linear combination of eigenvectors, and the coefficients of this combination will be the new face represented in the eigenspace.

The Linear Discriminant Analysis (LDA) searches for those vectors in the underlying space that best discriminate among classes (rather than those that best describe the data). More formally, given a number of independent features relative to which the data is described, LDA creates a linear combination of these which yields the largest mean differences between the desired classes.
The SOM nets are auto-organized maps constituted by neurons on a flat structures either 1-D or 2-D. The learning method is based on "competitive learning", whose purpose is to discover patterns into input data. An input vector of arbitrary dimension is taken in a discrete neuron map in accordance with the proximity of the patterns in the original dimension [2].

2 Methodology

Training phase diagram is showed in the figure 1. The diagram shows the stages related to the construction of PCA subspace and LDA subspace based on the training samples and the classification stage implemented by individual SOM neural nets.

![Training phase diagram](image)

**Figure 1. Proposed algorithm - training phase.**

The training stage of LDA module is built after the calculation of the coefficients related to each projected face in the PCA subspace. The weights of one same class (or coefficients LDA of the faces of one exactly individual in the training) feed an only SOM neural net representing the class.

The ORL database made by *Olivetti Research Laboratory in Cambridge*, UK, with 10 different images of 40 distinct individuals (total of 400 images) was applied to evaluate the performance of the presented system (figure 2). Increasing the size database, the images have been flipped horizontally to produce more 400 images.

![Example of faces](image)

**Figure 2. Example of faces in the face database.**

3 Experiments

To evaluate the PCA and LDA interaction, we proposed to analyze the PCA and LDA algorithm’s performance, choosing the eigenvectors interval, which define from 60% to 99% of the energy amount to construct the PCA subspace and from 70% to 90% to the LDA, varying the eigenvectors number by 2 for the PCA and considering all the eigenvectors included into the LDA energy interval.

We made a random selection with equal possibilities among the 20 faces to each particular person, performing different test and training groups that were submitted to the algorithm to elaborate the
efficiency and interaction curves between PCA and LDA. Six different combinations of the selected faces to training were evaluated, creating groups with 5, 6, 7, 8, 9 and 10 faces of each individual, and the remnant ones were used to constitute the test group. Looking for improving the test confidence, we performed 10 times the same test for each combination, enabling us to construct an average result with a 95% confidence interval, supposing a normal distribution (t-student) to the random faces selection over the recognition rates.

In figures 3, 4, 5, 6, 7 and 8 are showed the recognition rates acquired to the PCA + LDA, varying the quantity of PCA eigenvectors to build a subspace with the early defined energy limits, and using the Euclidian distance as classifier. Each PCA subspace generates a greatly variety of LDA subspaces combination, represented by the LDA eigenvectors included in the pre-defined energy interval, but the graphics show only the combinations that resulted in the maximum recognition rate for each PCA subspace.

Analyzing the graphics showed by figures 3, 4, 5, 6, 7 and 8, we obtain some characteristics about the applied algorithm in the proposed database. Following below there are more details:

1. The results related to the PCA stage revealed a transitory phase followed by one phase with stationary recognition rates, and the last eigenvectors do not carry meaningful information to the global training group.

2. LDA stage was able to increase recognition rates over the PCA.

3. An intrinsic deficiency related to the LDA method can be observed in figures 4 and 5, when we have few training samples to each individual class with a large number of PCA eigenvectors.

4. the recognition rates pikes to the PCA method are not the same for the LDA.

To analyze the recognition rates behavior to the LDA subspace + SOM algorithm over the LDA eigenvectors (considering the limits of energy concentration in the subspace), we picked some PCA
subspaces near to the region that had the biggest recognition rates of the algorithm. Figure 9 shows the results.

Figure 9. LDA + SOM algorithm (8 faces of training).

4 Conclusions

The purpose of this work has been to classify/identify one face with its respective representative on the database connecting to the particular individual (one-to-many application). A computational system to face recognition was implemented based in results showed by recent techniques using the LDA subspace algorithm (holistic method) to codify the images, and many SOM neural networks together to classify the faces set.

Formalizing the LDA subspace method, LDA and PCA stages are much important to construct a high-performance algorithm to face recognition. The tests were performed with many training groups, and the results showed that there is no need to use all the PCA eigenvectors to reach high recognition rates (nearly to 97% to the ORL face database).

References